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# MINING FACEBOOK PAGE FOR BI-PARTISAN ANALYSIS

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# MINING FACEBOOK PAGE FOR BI-PARTISAN ANALYSIS

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## ABSTRACT

Social media, particularly Facebook, has become ubiquitous in everyday life. Almost all news sources have adopted Facebook as a platform for dissemination of news. There are many opinions and studies on the partisanship of journalism. What makes social media interesting is that people do not only consume but also interact with others centered around a news article or post. Depending on the partisan bias of both the provider and the consumer, the interactions, and thus the conversation may vary. This research is a preliminary step towards mining these interactions and conversations pivoted against the topic of “fake news” from CNN and Fox News. We used several techniques of data mining, data analytics, and text analytics to generate summaries and descriptive statistics to explore user behavior. Our findings suggest that CNN follower base is more interactive and gregarious. Additionally, CNN followers’ use of Facebook reactions is more diverse, favoring the “haha” (funny / sarcastic) reaction, while those on Fox News’ inclined more towards “like” and “love” (agreement).

## Keywords

Facebook, social media, comment analysis, political bias, partisan news media

## INTRODUCTION

Over the years, Facebook has become a popular platform for many news media outlets to engage their audience. Unlike traditional media, news consumptions through social media are more gratifying (Lee et al., 2012). Social media has made news a participatory ecosystem (Hermida, 2010). On Facebook, people are able to respond to news articles and express their opinion through comments and reactions (e.g. single click emotional response feature on Facebook).

In addition to their response, people can also engage in conversations with other users through multi-level comments. Comments have two levels – a response to the article (post), and a reply to a comment on the post. Responses to comments are grouped under the respective comment as a thread. Conversation threads become interesting when users have conflicting views with the article posted, or with the opinion of another user. This research aims to explore the conversations on posts and analyze user behavior on controversial articles on opposing partisan news media pages.

There has always been a perceived bias or viewpoint based on the media outlet delivering a story (Eveland & Shah, 2003; Giner-Sorolla & Chaiken, 1994). The perceived bias of the media outlet also contributes to how audiences react to content which interacts either positively or negatively depending on their personal biases toward the story content. People tend to agree with and perceive the quality of posts as being higher if their personal bias aligns with the perceived bias of the source (Gentzkow & Shapiro, 2006).

Given this perspective, we would like to first investigate how comment behavior varies between politically biased media outlets. We will focus on the words used, length of responses, how quickly people respond, and how long does each conversation last. We would also like to compare the reactions on each post to hypothesize the perceptions of users towards each post.

## LITERATURE REVIEW

### Political Bias in news media

There are long-standing debates on political bias of news media outlets (Morris, 2007). Numerous empirical studies over the past few decades have failed to find any substantial evidence on the partisan bias (Domke et al., 1997; Shah et al., 1999; Waldman & Devitt, 1998). This perceived media bias is, for the most part, counter attitudinal - Republicans feel that popular news media is liberal biased, and the Democrats believe it favors conservatism (Eveland & Shah, 2003; Giner-Sorolla & Chaiken, 1994). However, in recent times, with the ubiquity of the Internet and social media, methods of news consumption have changed dramatically.

### News Outlets in Social Media changes things

Traditional news media outlets such as TV, radio, newspaper do not provide the audiences the ability to filter and/or respond to the content (Hermida, 2010). Social network sites (SNS) provide users with the agency on when, what, and from whom to consume information (Weeks & Holbert, 2013). Social network sites like Facebook and Twitter are increasingly getting popular

for dissemination and consumption of news (Oeldorf-Hirsch & Sundar, 2015). In Facebook, for example, news organizations can set up pages which users follow (subscribe to) (Weeks & Holbert, 2013). This enables users to seek information they agree with and in turn incentivize news organizations towards selective curation (Mullainathan & Schleifer, 2005). The selectivity of news reinforces existing ideologies and views (Lyengar & Hahn, 2009). This eventually creates a Spiral of Silence (Noelle-Neumann, 1993) for anyone with opposing views - a phenomenon where the climate of public opinion accumulates from the plethora of opinions in a public discourse silencing those whose views differ. This effectively enables and bolsters the political bias associated with the news outlet. People with a conflicting bias to that of the news outlet tends to form a negative opinion of the content (Gentzkow & Shapiro, 2006).

### Public Interactions on Social Media

In an SNS environment such as that of a Facebook page, people not only consume information, they also disperse the information through features provided by the platform (Weeks & Holbert, 2013). Facebook facilitate interactions through comments, sharing, and the “like” button (Oeldorf-Hirsch & Sundar, 2015, Shen et al., 2015). Receiving a “like” on a post reflect users’ recommendation or agreement of the post. However, in recent times, the “like” feature of Facebook has expanded to “reactions”. Users can express emotions by reacting to a post by denoting any one of five reactions - like, love, sadness, anger and two forms of amusement (‘haha’ and ‘wow’) (see Figure 1).

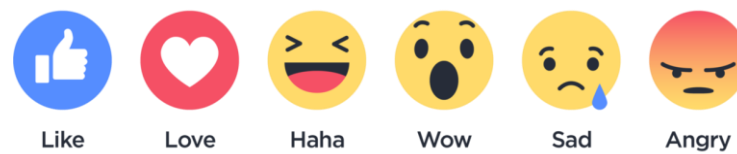


Figure 1. Facebook reactions

Users have the option to ‘reply’ to each comment forming multiple discussion threads within each post. Additionally, the “reactions” feature allows users to either endorse or express disapproval to the opinions posted on the post, each comment, and each reply. Comment behavior varies in Facebook depending on the personality type of the user and the post (Oeldorf-Hirsch & Sundar, 2015). While introverted personalities post longer and strongly subjective comments with negative connotations, an extroverted individual will engage positively with other users (Shen et al., 2015)

### METHOD

To answer our questions, we applied a data mining approach to user comments collected in response to two different news media outlets posting similar news stories on the social media platform. The data is collected using the Facebook Graph API for news posts into a data warehouse (see Figure 2).

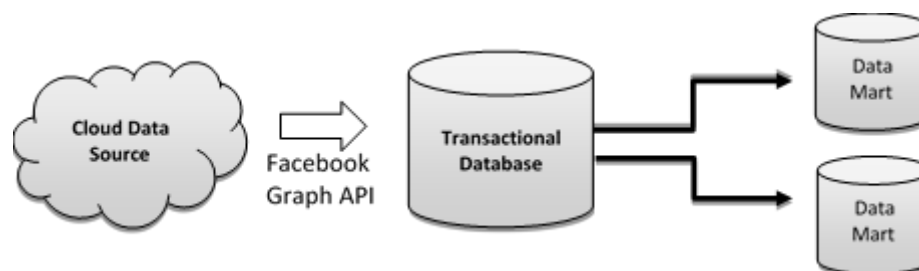


Figure 2. Data Modeling

Included in the dataset are user reactions to the post, comments, replies, and reactions to both comments and replies. For our analysis of the data, we apply techniques of natural language processing such as n-gram identification, term frequency analysis, and document summarization to determining the primary contents in the post, the top-level comments, and each comment thread.

**ANALYSIS AND RESULTS**

For this study, we wanted to see how people with different political bias react to similar news stories on politically dissimilar news outlets. We selected two articles on the topic of “fake news” one from CNN, commonly left leaning, and one from Fox News, commonly right leaning.



**Figure 3. CNN Story**



**Figure 4. Fox News Story**

For each article, we queried the data mart and generated two reports for analysis. The report consisted of the following parameters:

- *Source Title*: Name of the news outlet
- *Source ID*: Page ID of the news outlet
- *Story Title*: Title of the article
- *Post Created Time*: Time an article was posted Facebook
- *Comments*: Comments on the post
- *Comment Time*: Time of comment creation
- *Commenter ID*: The ID of the commenter
- *Replies*: Replies to each comment
- *Reply Time*: Time when the reply is posted
- *Reply ID*: The ID of the reply

We applied technique of text analytics to conducted *descriptive analytics and exploratory analysis* on the data set. The following sections discusses about these analyses.

**Descriptive Analytics**

For the descriptive analysis, we calculated the total number of comments, total number of replies, the reply density, the highest number of replies to a comment, and the count of reactions to each post as shows in Table 1.

	CNN	FOX News
Total Comments	58	30
Total Replies	191	83
Total Reaction	949	674
Reply Density (Total reply/ Unique Comments)	5.655172	4.7

**Table 1. Descriptive Statistics**

Table 2 shows the reaction types and their frequency against their respective news outlet.

Reactions	CNN	Fox News
Like	648	550
Haha	190	27
Love	55	89
Wow	33	5
Angry	13	3
Sad	10	0

**Table 2. Count of reactions**

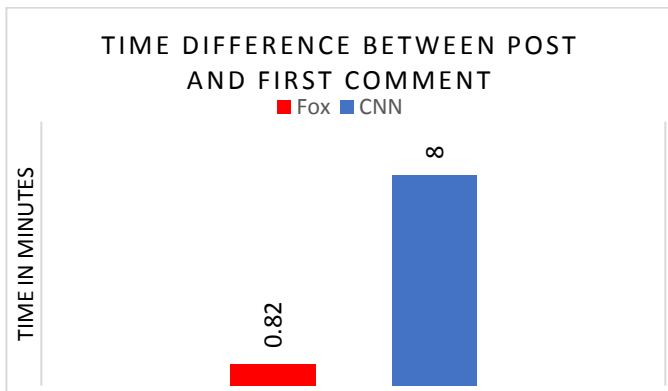
From the tables, we see both the number of comments and replies on CNN’s post is larger than that on Fox News’s post. The reply density reflects the follower’s engagement with the conversations in the thread. Since the average reply per comment is higher, this may suggest CNN’s follower base is more engaged in the conversation. Both post of CNN and Fox News received significant numbers of reactions, however the total for CNN was greater than for Fox News. We observe a variation in the reaction type and count in the two pages. CNN’s post on fake news got more ‘haha’ while Fox News’ article got more ‘Love’. However, the statistics from the analysis section indicate Fox News’s post received only 4 kinds of reactions whereas CNN received all 6.

**User’s Interaction with the post**

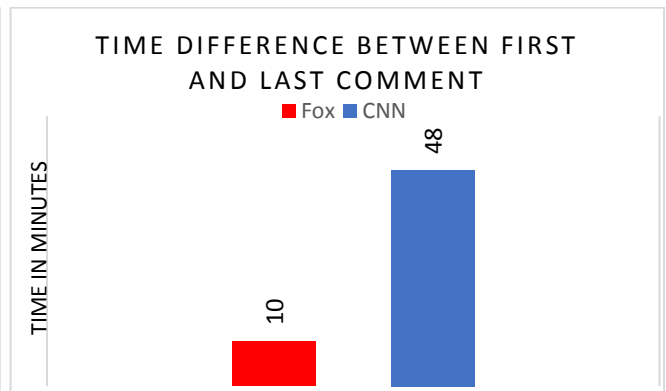
To compare engagement on either news outlet based on the articles on “fake news” we calculated the following.

- Time difference between posting the article and first comment
- Time difference between the first and the last comment

From each of these metrics we aim to determine any differences in the responsiveness and engagement towards the news articles between the two audience groups. However, we do have to take into consideration that reaction may vary depending on news articles and not necessarily due to the source of news. The following bar charts illustrate the comment time and the duration of conversation:



**Figure 5. Interaction with post**



**Figure 6. Interaction amongst users**

From analyzing the user’s interaction, we see only a 49 second time difference between the first comment and the article on Fox. In case of CNN, there was an 8-minute gap. However, the conversation in Fox News (time difference between first and last comment) lasted for 14 minutes, while CNN’s lasted 38 minutes.

**Text Analytics: Term Frequency Calculation**

To determine the topics frequently mentioned by the two media sources, we conducted term frequency analysis and extracted the number of times each word appear throughout the corpus of comments and replies. Through this analysis, we intend on finding the primary focus of people from different partisan biased outlets when conversing about the topic of “fake news” and the point of conflict between the two groups. Finally, we generated word clouds for the frequent terms used as can be seen in Figure 7.



Figure 7. Word cloud from term frequency analysis

Although the outcome of term frequency analysis is diverse, we noticed CNN’s follower refer to previous president and presidential candidate whilst Fox’s followers mentioned words such as “dead”, “liar”, “republican party” etc.

## DISCUSSION

The analysis shows that CNN follower base tends to interact a lot more with the posts than the Fox News followers. In addition, CNN posts tend to garner longer discussion threads that span over an extended period. On the other hand, conversations and reactions on Fox News are very erratic and as we can also see from the term frequency analysis, repetitive. While on the topic of Fake News, it seems CNN followers refers to previous predecessors in office and Fox News followers speaks about “republican party” and “dead”. This study has given us some insight on what people talk about when it comes to the topic of Fake News it has formed the ground for further exploration towards finding the rationale behind their opinions.

## CONCLUSION AND FUTURE WORK

We ran an exploratory analysis on the topic of fake news as perceived by followers of CNN and Fox News. We conducted term frequency analysis to determine what people were talking about, found user’s interaction with the posts and each other and basic descriptive statistics. Further research using the results to conduct experiment that can contribute to explain the topics people mentioned frequently and overall nature of partisan behavior on conflicting ideologies.

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